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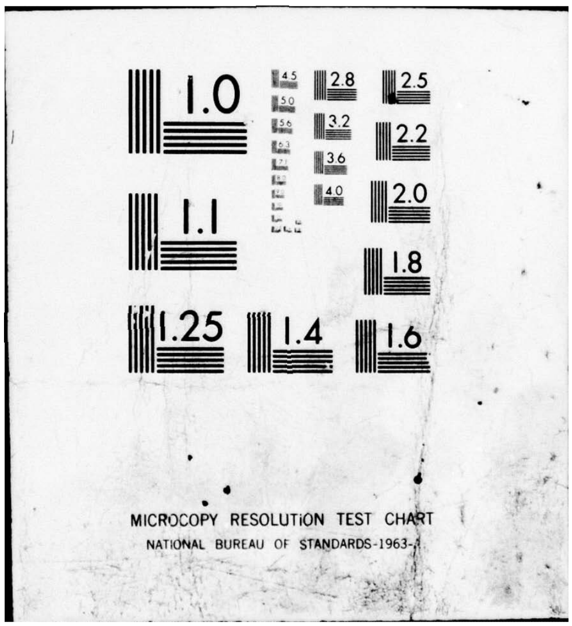
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July, 1979

IMAGE MODELS

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ABSTRACT

This paper reviews pixel-based and region-based ("structural") image models. The former include both one-dimensional time series and random field models, with the properties of the field specified either locally or globally.

The support of the U.S. Air Force Office of Scientific Research under Grant AFOSR-77-3271 is gratefully acknowledged, as is the help of Kathryn Riley in preparing this paper.

1. Types of Models

Traditionally, image models have been classified as statistical or structural [22,48,54]. The statistical models involve desription of image statistics such as autocorrelation etc., while the structural approach consists of specification of structural primitives and placement rules for laying these primitives out in the plane. It should be noted that if the rules in the structural approach are not statistical, the resulting models should be too regular to be interesting. Thus the structural models too must in part be statistical. A better classification of image models might be as follows:

a) Pixel based models: These models view individual pixels as the primitives of the texture. Specification of the characteristics of the spatial distribution of pixel properties [22,42] constitutes the texture description.

b) Region based models: These models conceive of a texture as an arrangement of a set of spatial (sub)patterns according to certain placement rules [54]. Both the subpatterns and their placement may be statistically characterized. The subpatterns may further be made up of smaller patterns.

In the following sections we will discuss these two classes of models and review many of the studies of image modeling conducted through 1978. It should be emphasized that image modeling is a rapidly evolving field and much further work is currently in progress.

2. Pixel Based Models

Pixel based models can be further divided into two classes:

2.1. One-Dimensional Time Series Models

Time series analysis [10] has been extensively used [38, 60,61] to study visual textures. The image is TV scanned to provide a one-dimensional series of gray level fluctuations, which is treated as a one-dimensional stochastic process evolving in "time". The future course of the process is presumed to be predictable by knowing enough about its past.

Before summarizing the models, we review some of the commonly used notation in time series.

Let

$$\ldots\ Z_{t-1}\ Z_t\ Z_{t+1}\ \ldots$$

be a discrete time series where Z_i is the value of the random variable Z at time i. We denote the series by [Z].

Let μ be the mean of [Z], called the "level" of the process.

Let $[\tilde{Z}]$ denote the series of deviations about μ, i.e.,

$$\tilde{Z}_i = Z_i - \mu$$

Let [a] be a series of outputs of a white noise source, with mean zero and variance σ_a^2.

Let B be the "backward" shift operator such that $B\,\tilde{Z}_t = \tilde{Z}_{t-1}$; hence

$$B^m\,\tilde{Z}_t = \tilde{Z}_{t-m};$$

and let ∇ be the "backward" difference operator such that

$$\nabla\tilde{Z}_t = \tilde{Z}_t - \tilde{Z}_{t-1} = (1-B)\tilde{Z}_t;$$

hence $\nabla^m\tilde{Z}_t = (1-B)^m\tilde{Z}_t$

The dependence of the current value $\tilde{Z}_t$ of the random variable $\tilde{Z}$ on the past values of $\tilde{Z}$ and a is expressed in different ways, and this gives rise to several different models [38].

(a) Autoregressive Model (AR):

In this model the current $\tilde{Z}$-value depends on the previous p $\tilde{Z}$-values, and on the current noise term:

$$\tilde{Z}_t = \phi_1\tilde{Z}_{t-1} + \phi_2\tilde{Z}_{t-2} + \ldots + \phi_p\tilde{Z}_{t-p} + a_t \tag{1}$$

If we let

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$

then (1) becomes

$$[\phi_p(B)]\;(\tilde{Z}_t) = a_t$$

$[\tilde{Z}]$, as defined above, is known as the autoregressive process of order p, and $\phi_p(B)$ as the autoregressive operator of order p. The name "autoregressive" comes from the model's similarity to regression analysis, and the fact that the variable $\tilde{Z}$ is being regressed on previous values of itself.

(b) Moving Average Model (MA):

In (a) above, $\tilde{Z}_{t-1}$ can be eliminated from the expression for $\tilde{Z}_t$ by substituting

$$\tilde{Z}_{t-1} = \phi_1\tilde{Z}_{t-2} + \phi_2\tilde{Z}_{t-3} + \ldots + \phi_p\tilde{Z}_{t-p-1} + a_{t-1}$$

This process can be repeated to yield eventually an expression for $\tilde{z}_t$ as an infinite series in the a's.

The moving average model allows a finite number q of previous a-values in the expression for $\tilde{z}_t$. This explicitly treats the series as being observations on linearly filtered Gaussian noise.

Letting

$$\theta_q(B) = 1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q,$$

we have

$$\tilde{z}_t = [\theta_q(B)](a_t)$$

as the <u>moving average process of order</u> q.

(c) <u>Mixed Model</u> (ARMA):

To achieve greater flexibility in fitting of actual time series, this model includes both the autoregressive and the moving average terms. Thus

$$\tilde{z}_t = \phi_1\tilde{z}_{t-1} + \phi_2\tilde{z}_{t-2} +\ldots+ \phi_p\tilde{z}_{t-p} + a_t-\theta_1 a_{t-1}-\theta_2 a_{t-2}-\ldots-\theta_q a_{t-q}$$

i.e., $[\phi_p(B)](\tilde{z}_t) = [\theta_q(B)](a_t)$ (2)

In all the three models just mentioned, the process generating the series is assumed to be in equilibrium about a constant mean level. Such models are called <u>stationary models</u>.

There is another class of models called <u>non-stationary models</u>, in which the level μ does not remain constant. The series involved may, nevertheless, exhibit homogeneous behavior when the differences due to level-drift are accounted for. It can been shown [10] that such a behavior may be represented by a generalized autoregressive operator.

A time series may show a repetitive pattern of periods of similar characteristics. For example, in the TV scan of an image the intervals corresponding to rows will have similar characteristics. A generalized model that incorporates the presence of such "seasonal effects" in the time series can also be obtained [38].

All of the time series models discussed above are unilateral, i.e., a pixel depends only upon the pixels that precede it in a TV scan. Any introduction of bilateral dependence gives rise to more complex parameter estimation problems, even though both conditional representations are known to be essentially identical [9,12]. It may be of interest to note that a frequency domain treatment makes parameter estimation in bilateral representation much easier [13].

2.2. Random Field Models

These models treat the image as a two-dimensional random field [53,64]. The models make use of the properties of the grid that defines the pixel locations. We will consider two subclasses of these models.

2.2.1. Global Models

Global models attempt a description of the field by specifying a process that can be used to obtain a realization of the set of gray level values at various pixels, or by specifying particular properties of the field.

An important model has been used by oceanographers [31-33, 49] interested in the patterns formed by waves on the ocean surface. Longuet-Higgins [31-33] treats the ocean surface as a random field satisfying the following assumptions:

(a) the wave spectrum contains a single narrow band of frequencies, and

(b) the wave energy is being received from a large number of different sources whose phases are random.

Considering such a random field, he obtains [32] the statistical distribution of wave heights, and derives relations between the root mean square wave height, the mean height of the highest p% of the waves, and the most likely height of the largest wave in a given interval of time.

In subsequent papers [31,32], Longuet-Higgins obtains an additional set of statistical relations among the parameters describing (a) a random moving Gaussian surface [31], and (b) a Gaussian isotropic surface [32].

Some of the results that he derives are:

(1) the probability distribution of the surface elevation, and that of the magnitude and orientation of the gradient,

(2) the average number of zero crossings per unit distance along a line in an arbitrary direction,

(3) the average length of contour per unit area,

(4) the average density of maxima and minima per unit area, and

(5) for a narrow spectrum, the probability distribution of the heights of maxima and minima.

All the results are expressed in terms of the two-dimensional energy spectrum up to a finite order only. The converse of the problem is also studied and solved, i.e., given certain statistical properties of the surface, to find a convergent sequence of approximations to the energy spectrum.

The analogy between this work and image processing, and the significance of the results obtained therein, is obvious. Fortunately the assumptions made are also acceptable for images.

Schachter [57] suggests a version of the above model for the case of a narrow band spectrum. Panda [47] uses an analogous approach to analyze background regions selected from Forward Looking InfraRed (FLIR) imagery. He derives expressions for (a) density of border points and (b) average number of connected components in a row of the thresholded picture. There is good agreement between the observed and the predicted values in most cases, for most of the pictures considered. Panda [46] also uses the same model to predict the properties of the pictures obtained by running several edge operators (based on differences of average gray levels) on some synthetic pictures with normally distributed gray levels, and having different correlation coefficients. The images are assumed to be continuous-valued stationary Gaussian random fields with continuous parameters.

Nahi and Jahanshashi [43] suggest modelling the image as a background statistical process combined with a set of foreground statistical processes, each replacing the background in the regions occupied by the objects of the category which it is assumed to characterize. In estimating the boundaries of horizontally convex objects on a background in noisy binary pictures, Nahi and Jahanshahi assume that the two kinds of regions in the picture are formed by two statistically independent stationary random processes with known (estimated) first two moments. However, the borders of the regions covered by the different statistical processes are modelled locally. Specifically, the end-points of the intercepts of the given object on successive rows are assumed to form a first order Markov process. This model thus also involves local interactions.

Thus, using the notation

$b(m,n)$ = gray level at the nth column of the mth row

$\gamma(m,n)$ = a binary function carrying the boundary information

b_b = a sample gray level from the background process,

b_o = a sample gray level from the object process, and

ν = a sample gray level from the noise process,

the model allows us to write

$$b(m,n) = \gamma(m,n)\ b_o(m,n) + [1-\gamma(m,n)]\ b_b(m,n) + \nu(m,n)$$

where γ incorporates the Markov constraints on the object boundaries.

In a subsequent paper Nahi and Lopez-Mora [44] use a more complex γ function. For each row, γ either indicates the absence of the object or provides a vector estimate of the object width and its geometric center in that row. The two-dimensional vector possesses information about the object size and skewness, and is assumed to be a first-order Markov process.

Pratt and Faugeras [50] and Gagalowicz [17] view texture as the output of a homogeneous spatial filter excited by white noise, not necessarily Gaussian. The image is then characterized by its mean, the histogram of the input white noise, and the transfer function of the filter. For a given texture, the model parameters are obtained as follows:

- The mean is readily estimated from the image.
- Computing the autocorrelation function (second-order moments) determines the magnitude of the transfer function.

- Computing higher-order moments determines the phase of the transfer function.

Inverse filtering gives the white noise image and hence its histogram and probability density. For example, for a Markov field of order 1 it may be sufficient to replace the decorrelation operator by a Laplacian, or by gradient operators [50]. However, the whitened field estimate of the independent identically distributed noise process obtained above will identify only the spatial operator in terms of the autocorrelation function, which is not unique. Thus the white noise probability density and the spatial filter do not, in general, make up a complete set of descriptors [51]. But it may be possible that they are sufficient descriptors from the standpoint of visual texture.

Several authors have proposed models for random surfaces or random height fields [2,16,35]. In a discussion on surface patterns in geography Freiberger and Grenander [16] argue that the earth height field is usually too irregular to be described by an analytic function of the coordinates with a small number of free parameters. However the irregularity cannot be expressed by pure randomness either since it is characterized by strong continuity properties. He therefore suggests the use of stochastic processes derived from physical principles. Mandelbrot [35] and Adler [2] discuss a Brownian surface model.

The representations of signals in one-dimensional signal processing that yield recursive solutions motivate the use of differential (difference) equations in two dimensions [29]. Jain [29] represents images by random fields of one of three different kinds, characterized by the three different classes of partial differential equations, describing a digital shape by an appropriate finite difference approximation of a partial differential equation (PDE). The class of hyperbolic PDE's is shown to provide more general causal models than autoregressive moving average models. For a given spectral density function (or covariance function), parabolic PDE's can provide causal, semicausal, and even noncausal representations. Finally, elliptic PDE's provide noncausal models that represent two-dimensional discrete Markov fields. They can be used to represent both isotropic and nonisotropic images.

Jain [29] argues that the well established theory of PDE's and their numerical solutions and the availability of many computer algorithms make PDE representation useful. This representation also obviates the need for spectral factorization which removes the restriction of separate covariance functions. System identification techniques may be considered for choosing a PDE model for a given class of images.

Angel and Jain [8] use the diffusion equation to model the spread of values around any given point. Thus a given image is viewed as a blurred version of some original image.

In the absence of any knowledge or assumption about the global process underlying a given image, one may attempt to describe the joint probability density of the properties (say, gray level) of the pixels, although this may be an overspecification, i.e., the modeling may not represent enough abstraction. It also implies estimation of the spatial probability density functions of gray levels, which means inference on the joint probability density of a large number of random variables corresponding to the pixels in the entire image. To make the problem a little simpler, attempts have been made to use parametric models where the form of the probability density is assumed, or to model the field density by specifying some "important" properties of the field that may correspond to more than one probability density function.

Among parametric models of the joint density of pixels in a window, the multivariate normal has been the one most commonly used because of its tractability. However, it has been found to have limited applicability. For binary patterns, Abend et al. [1] discuss an iterative procedure to obtain an approximate estimate of the joint probability density function of the properties of pixels having a multivariate normal distribution, in terms of lower order marginals of this distribution. They argue that the multivariate normal approach is very limiting and that it requires special development when the sample covariance matrices are singular. Furthermore, the lower order marginals themselves have to be estimated based on samples which, in practice, are usually not numerous.

Hunt [25,26] also points out that stationary, Gaussian modeling of images is an oversimplification. Consider the vector F of the picture points obtained by concatenating them as in a TV scan. Let R_F be the covariance matrix of the gray levels in F. Then according to the Gaussian assumption, the probability density function of F is

$$\rho(F) = K \exp[-\tfrac{1}{2}(F-\bar{F})^T R_F^{-1}(F-\bar{F})]$$

where $\bar{F}$ = constant mean vector

R_F = covariance matrix

and K = normalizing constant

The stationarity assumption makes $\bar{F}$ a vector of identical components. This means that each point in the image has the same ensemble statistics. Images, however, seldom have a bell-shaped histogram.

A Gaussian model for any set of multivariate data, however, is the only model that is mathematically tractable to any reasonable extent. Hunt [25] proposes a nonstationary Gaussian model which differs from the stationary model only in that the mean vector $\bar{F}$ has unequal components. He shows the appropriateness of this model by subtracting, from each point on the image, its local ensemble average, and showing that the resulting picture fits a stationary Gaussian model.

Trussel and Kruger [62] show that the Laplacian density function constitutes a more valid model for high-pass filtered imagery than the Gaussian model. They show that this discrepancy neither seriously weakens the applicability of this class of models to a major restoration method, nor challenges any other conclusions of the work based on the Gaussian model.

Matheron [37] uses the change in pixel properties as a function of distance to model a random field. He uses the term "regionalized variables" to emphasize the particular features of the pixels whose complex mutual correlation reflects the structure of the underlying phenomenon. He assumes weak stationarity of the increments in the gray levels between pixels. The second moment of the increments for pixels at an arbitrary distance, called the variogram, is used to reflect the structure of the field. Knowledge of the variogram is useful for the estimates of many global and local properties of the field. Huijbregts [24] discusses several properties of the variogram and relates them to the structural features of the regionalized variables. For nonhomogeneous fields having spatially varying mean, the variogram of the residuals with respect to the local means is used.

A characterization similar to the variogram is given by the autocorrelation function. In work on image restoration, images have often been modelled by a two-dimensional random field with a given mean and autocorrelation. The following general expression has been suggested for the autocorrelation function:

$$R(\tau_1,\tau_2) = \sigma^2 \cdot \rho^{[-\alpha_1|\tau_1|-\alpha_2|\tau_1|]}$$

which is stationary and separable. Specifically, the exponential autocorrelation function (ρ=e) has been found to be reasonably good for a variety of pictorial data [15,18,23, 27,30].

Another autocorrelation model often cited as being more realistic is

$$R(\tau_1,\tau_2) = \rho^{\sqrt{\tau_1^2 + \tau_2^2}}$$

which is isotropic, rotation invariant and not separable.

2.2.2. Local Models

A simplification that could be introduced to reduce the problems involved in the joint probability specification for the entire image, as is necessary for the global models, is to assume that not all points in an image are simultaneously constrained by a high-dimensional probability density function, but that this is only true of small neighborhoods of pixels. However, even for a neighborhood of size 3x3 (or 5x5) and nonparametric representation one has to deal with densities in a 9 (or 25) dimensional space, along with the associated sample size and storage problems. This makes the approach unwieldy.

Read and Jayaramamurthy [52] and McCormick and Jayaramamurthy [39] make use of switching theory techniques to identify textures by describing their local gray level patterns using minimal functions. If each pixel can take one out of N_g gray levels then a given neighborhood of n pixels from an image can be represented by a point in an $n \times N_g$ dimensional space. If many such neighborhoods from a given texture are considered then they are likely to provide a cluster of points in the above space. The differences in the local characteristics of different textures are expected to result in different clusters. The set covering theory of Michalski and McCormick [40], which is a generalization of the minimization machinery of switching theory already available, is used [39,52] to describe the sets of points in each cluster. These maximal descriptions also allow coverage of empty spaces within and around clusters, and thus the samples do not have to be exhaustive but only have to be large enough to provide a good representation of the underlying texture.

Haralick et al. [20] confine the local descriptions to 2x1 neighborhoods. They identify a texture by the gray-level cooccurrence frequencies at neighboring pixels, which are the first estimates of the corresponding probabilities. They use several different features, all derived from the co-occurrence matrix, for texture classification.

Most of the local models, however, use conditional properties of pixels within a window, instead of their joint probability distributions as in the local models discussed above. We will now discuss these Markov models that make a pixel depend upon its neighbors.

Time series analysis for the one-dimensional models discussed earlier can also be used to capture part of the two-dimensional dependence, without getting into the analytical problems arising from a bilateral representation. Tou et al. [60] have done this by making a point depend on the points in the quadrant above it and to its left. For such a case, the autoregressive process of order (q,p) is

$$\tilde{z}_{ij} = \phi_{01}\,\tilde{z}_{i,j-1} + \phi_{10}\,\tilde{z}_{i-1,j} + \phi_{11}\,\tilde{z}_{i-1,j-1} + \ldots + \phi_{qp}\,\tilde{z}_{i-q,j-p};$$

the moving average process of order (q,p) is

$$\tilde{z}_{ij} = a_{ij} - \theta_{01}a_{i,j-1} - \theta_{10}\,a_{i-1,j} - \theta_{11}\,a_{i-1,j-1} - \ldots - \theta_{qp}\,a_{i-q,j-p};$$

and the two-dimensional mixed autoregressive/moving average process is

$$\tilde{z}_{ij} = \phi_{01}\,\tilde{z}_{i,j-1} + \phi_{10}\,\tilde{z}_{i-1,j} + \phi_{11}\,\tilde{z}_{i-1,j-1} + \ldots + \phi_{qp}\,\tilde{z}_{i-q,j-p}$$
$$+ a_{ij} - \theta_{01}\,a_{i,j-1} - \theta_{10}\,a_{i-1,j} - \theta_{11}\,a_{i-1,j-1} - \ldots$$
$$- \theta_{rs}\,a_{i-r,j-s}$$

The model, in general, gives a nonseparable autocorrelation function. If the coefficients of the process satisfy the condition

$$\phi_{mn} = \phi_{m0}\,\phi_{0n}$$

then the process becomes a multiplicative process in which the influence of rows and columns on the autocorrelation is separable. Thus

$$\rho_{ij} = \rho_{i0}\,\rho_{0j}$$

Tou et al. consider fitting a model to a given texture. The choice among the autoregressive, moving average and mixed models, as well as the choice of the order of the process, is made by comparing the behavior of some observed statistical properties, e.g., the autocorrelation function, with that predicted by each of the different models. For each of the possibly many choices of models, the values of the parameters are determined so as to minimize, say, the least square error in fit.

A comparison of the predictions of autocorrelation function, results of transformations of the series, etc., based upon the model obtained above, with similar properties of the available data can be used to establish its appropriateness, or to suggest desirable modifications in the model, e.g., changing the order, etc.

In a subsequent paper, Tou and Chang [61] use the maximum likelihood principle to optimize the values of the parameters, in order to obtain a refinement of the preliminary model as suggested by the autocorrelation function.

A bilateral dependence in two dimensions is more complex as compared to the one-dimensional case discussed earlier. Once again, this general formulation has a unilateral counterpart; for example, making a point depend on the points in the rows above it, as well as the points to its left on its own row. However, Whittle [63] gives the following reasons in recommending working with the original two-dimensional model:

1) The dependence on a finite number of lattice neighbors, for example a finite autoregression in two dimensions, may not always have a unilateral representation that is also a finite autoregression.

2) The real usefulness of the unilateral representation is that it suggests a simplifying change of parameters. For most two-dimensional models, however, the appropriate transformation, even if evident, is so complicated that nothing is gained by performing it. It may be pointed out that frequency domain analysis for parameter estimation [13] may prove useful here too.

Two-dimensional Markov random fields have been investigated for representing textures. A wide sense Markov field representation aims at obtaining linear dependence of a pixel property, say its gray level, on the gray levels of certain other pixels so as to minimize, say, the mean square error between the actual and the estimated values such that the error terms of various pixels are uncorrelated random variables. A strict sense Markov field representation involves specification of the probability distribution of the gray level given the gray levels of certain other pixels. Although processes of both these types have been investigated, more experimental work has been done on the former.

Woods [65] shows that the strict sense Markov field differs from a wide sense field only in that the error variables in the former have a specific correlation structure, whereas the errors in the latter are uncorrelated. He points out the restriction on the nonwhite noise (error) process driving the strict sense model that yields a recognizable field. The condition under which a general noncausal Markov independence reduces to a causal one is also specified.

Abend et al. [1] introduce Markov meshes to model dependence of a pixel on a certain immediate neighborhood. The joint probability density for the entire image, then, is the product of local conditional probability densities at each pixel. Using Markov chain methods on the sequences of pixels from various causal dependency neighborhoods of a pixel they show that in many cases such a causal dependence translates into a noncausal dependence. For example, the dependence of a pixel on its west, northwest and north neighbors translates into its dependence upon all its eight neighbors. Interestingly, the causal neighborhood that results in a 4-neighbor noncausal dependence is not known in the formulation, although in the Gauss Markov formulation of Woods [65] such an explicit dependence is allowed. In this sense Woods' definition of a Markov field is more general than the Markov meshes of Abend et al. [1].

Hassner and Sklansky [21] also discuss a Markov random field model for images. They present an algorithm that generates a texture from an initial random configuration and a set of independent parameters that specify a consistent collection of nearest neighbor conditional probabilities which characterize the Markov random field.

Deguchi and Morishita [14] use a noncausal model for the dependence of a pixel on its neighborhood centered at the pixel. The weights are determined by minimizing the mean square estimation error. The optimal two-dimensional estimator characterizes the texture. They use such a characterization for classification and for segmentation of images consisting of more than one textural region.

Jain and Angel [27] use 4-neighbor autoregression to model a given autocorrelation function, not necessarily separable. They obtain values of the autoregression coefficients in terms of the desired autocorrelation function, which does not have to be separable. However, their representation involves error terms that are uncorrelated with each other or with the non-noisy pixel gray level values. As pointed out by Panda and Kak [45], these two assumptions about the error terms are incompatible for Markov random fields. [65].

Jain and Angel [27] point out that a 4-neighbor Markov dependence can represent a large number of physical processes such as steady state diffusion, random walks, birth and death processes, etc. They also propose 8-neighbor [27] and 5-neighbor (the 8 neighbors excluding the northeast, east, and southeast neighbors) [27,28] models.

Wong [64] discusses the characterization of second order random fields (having finite first and second moments) from the point of view of their possible use in representing images. He considers various properties of a two-dimensional random field, and their implications in terms of its second-order properties. Some of the results he obtains are as follows:

(1) There is no continuous Gaussian random field of two dimensions (or higher dimensions) which is both homogeneous and Markov (degree 1).

(2) If the covariance function is invariant under translation as well as rotation, then it can only depend upon the Euclidian distance. The second-order properties of such fields (Wong calls them <u>homogeneous</u>) are characterizable in terms of a single one-dimensional spectral distribution.

Wong generalizes his notion of homogeneity to include random fields that are not homogeneous, but can be easily transformed into homogeneous fields. Even this generalized class of fields is no more complicated than a one-dimensional stationary process.

Lu and Fu [34] identify the repetitive subpatterns in some highly regular textures from Brodatz [11] and design a local descriptor of the subpattern in an enumerative way by generating each of the pixels in the window individually. The subpattern description is done by specifying a grammar whose productions generate a window in several steps. For example, starting from the top left corner rows may be generated by a series of productions, while other productions will generate individual pixels within the rows. The grammar used may also be stochastic.

3. Region Based Models

The next few models use the notion of a structural primitive, although both the shapes of the primitives and the rules to generate the textures from the primitives may be specified statistically.

Matheron [36] and Serra [58] propose a model that views a binary texture as produced by a set of translations of a structural element. All locations of the structural elements such that the entire element lies within the foreground of the texture are identified. Note that there may be (narrow) regions which cannot be covered by any placement of the structural element, as all possible arrangements of the element that cover a given region may not lie completely within the foreground. Thus only an "eroded" version of the image can be spanned by the structural element which is used as the representation of the original image. Textural properties can be obtained by appropriately parameterizing the structure element. It is interesting to note that for a structural element consisting of two pixels at distance d, the area of the eroded image is the value of the autocovariance, at distance d, of the original image. More complicated structural elements would provide a generalized autocovariance function which has more structural information. Matheron and Serra show how the generalized covariance function can be used to obtain various texture features.

Zucker [67] conceives of a real texture as being a distortion of an ideal texture which is a spatial layout of primitives as cells in a regular or semiregular tessellation. Certain transformations are applied to the primitives to distort them to provide a realistic texture. The statistical nature of the texture can be provided through these transformation rules.

Yokoyama and Haralick [66] describe a growth process to synthesize textures. Their method consists of the following steps:

a) Mark some of the pixels in a clean image as seeds.

b) The seeds grow into curves called skeletons.

c) The skeletons thicken to become regions.

d) The pixels in the regions thus obtained are transformed into gray levels in the desired range.

3) A probabilistic transformation is applied, if desired, to modify the gray level cooccurrence probability in the final image.

The distribution processes in (a) and the growth processes in (b) and (c) can be deterministic or random. Yokoyama and Haralick's method, however, sums up to an ad hoc sequence of growth operations to generate a random pattern, since the dependence of the properties of the images generated on the nature of the underlying operations is not obtained. This makes the approach unsuitable for texture description or classification.

A class of models called mosaic models, based upon random, planar pattern generation processes, have been considered by Ahuja [2,3,4,5], Ahuja and Rosenfeld [6] and Schachter, Davis, and Rosenfeld [56]. Schachter and Ahuja [55] describe a set of random processes that produce a variety of interesting piecewise uniform random planar patterns having regions of different shapes and with different relative placement. These patterns are analyzed for various geometrical and topological properties of the components, and for the pixel correlation properties in terms of the model parameters [3,4,5,6]. Given an image and various feature values measured on it, the relations obtained above are used to select the appropriate model.

The syntactic model of Lu and Fu [34] discussed earlier can also be interpreted as a region based model, if the subpattern windows are viewed as the primitive regions.

We may point out that although the model used by Nahi and Jahanshahi [43] and Nahi and Lopez-Mora [44] discussed earlier is pixel based, the function γ carries information about the borders of various regions. Thus, under the constraint that all regions except the background are convex, the model can also be interpreted as a region based model.

4. Discussion

Region based models are inherently more powerful than pixel based models. For the case of images on grids this is easy to see. Consider a subpattern that consists of a single pixel. The region shapes are thus trivially specified. It is obvious that the region characteristics and their relative placement rules can be designed so as to mimic the pixel and joint pixel properties of a pixel based model, since both have control over the same set of primitives and can incorporate the same types of interactions. This shows that region based models are at least as powerful as pixel based models. On the other hand if we are dealing with images that are structured, i.e. that have planar clusters of pixels such that pixels within a cluster are related in a different way than pixels across clusters, then we must make such a provision in the model definition. Such a facility is unavailable in pixel based models, whereas the use of regions as primitives serves exactly this purpose. It should also be pointed out that region based models appear to be more appropriate for the representation of natural textures, which do usually consist of regions.

Many texture studies are basically technique oriented and describe ad hoc texture feature detection and classification schemes which are not based upon any underlying model of the texture. We do not discuss these here; see [19,41,59] and the references therein.

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Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: AFOSR-TR-79-1158	2. GOVT ACCESSION NO.
3. RECIPIENT'S CATALOG NUMBER	
4. TITLE (and Subtitle): IMAGE MODELS	5. TYPE OF REPORT & PERIOD COVERED: Interim rept.
	6. PERFORMING ORG. REPORT NUMBER: TR-781
7. AUTHOR(s): Narendra Ahuja, Azriel Rosenfeld	8. CONTRACT OR GRANT NUMBER(s): AFOSR-77-3271
9. PERFORMING ORGANIZATION NAME AND ADDRESS: Computer Vision Laboratory, University of Maryland, College Park, MD 20742	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: 61102F 2304/A2
11. CONTROLLING OFFICE NAME AND ADDRESS: Air Force Office of Scientific Research/NM, Bolling AFB, Washington, DC 20332	12. REPORT DATE: July 1979
	13. NUMBER OF PAGES: 36
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office): 38	15. SECURITY CLASS. (of this report): Unclassified
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Image processing
Image models
Time series
Random fields
Texture

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This paper reviews pixel-based and region-based ("structural") image models. The former include both one-dimensional time series and random field models, with the properties of the field specified either locally or globally.

DD FORM 1473, 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE

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